

Self Organizing Migration Algorithm with Curvelet Based Non Local Means Method For the Removal of Different Types of Noise

Sanjeev K Sharma
Associate Professor, Department of E&I
SATI, Vidisha (M.P.)
san0131966@gmail.com

Dr. Yogendra Kumar Jain
Professor and I/C HOD, Department of CSE
SATI, Vidisha (M.P.)
ykJain_p@yahoo.co.in

Abstract—This research focus on image sharpness and quality using a self-organizing migration algorithm (SOMA) with curvelet based nonlocal means (CNLM) denoising is presented. In this paper, first transform curvelet is using on the noisy image obtain image. Find the comparison of 2 pixels in the noisy picture which is evaluated depend on these curvelet produced pictures which include complementary picture capabilities at particularly excessive noise levels and the noisy picture at especially low noise levels. Then pixel comparison and noisy photograph are used to denoised end outcome found applying NLM technique. SOMA obtains better quality with the aid of varying threshold on the basis of image pixels. The threshold can be determined using lower and upper value of noisy image. Quantitative evaluations illustrate that the proposed scheme perform more enhanced than the other filters namely median filter (MF) progressive switching median filter (PSMF), NLM, CNLM denoising process in conditions of noise removal and detail protection. Using different parameters for example Peak Signal Noise Ratio (PSNR), means Structural Similarity Matrix (MSSIM) and SSIM for noise free image. It is illustrated that the improved scheme provides an excessive degree of noise removal whilst maintaining the edges and other information in the image. In this study, algorithm is tested on dissimilar kind of noise explicitly, Random Valued Impulse Noise (RVIN), Gaussian Noise and Salt and Pepper (SNP) Noise with varying noise density from 10 to 90%. The proposed system proves better performance on high noise density.

Keywords— *SOMA, Impulse Noise, CNLM, PSNR, MSSIM, SSIM, PSMF, Median Filter, Gaussian Noise, Salt and Pepper Noise.*

I. INTRODUCTION

Denoising is the term of recapture version of data pixels from the noisy photograph model via smoothing it out with admire to its surrounding pixels. In photo processing (IP) that is very vital preprocessing step before these pictures are analyzed. Hyper spectral Imagery belongs to the faraway sensing region in which these pictures are remotely sensed with committed sensors. These sensors are designed to discover a worldwide distribution of object models from the target region, it captured or accumulated information or photos and provide to programs wherein those photo are studied [1]. In general, the obtained image is mostly useless with many types of noise or degradations or noise when the imaginary is

generated or in the process of transmission. Thus the corrupted image has necessity to be processed before they are used in some real applications. Those inverse problems contain image reconstruction, image restoration and image denoising [2].

II. NOISE MODEL

Type of Noise:

A. Impulse Noise

The model of impulse noise comprises two different impulse values with probability which is equal. These are the least and most pixel values of the taken into consideration integer c program language period (i.e., 0 and 255 for an 8-bit picture). The minimum pixel value, i.e., a black pixel is called poor impulse or salt and the maximum pixel price, i.e., a white pixel is known as high-quality impulse or pepper [3]. In RVIN noise is spread consistently. Dynamic range [0, 255] may take by RVIN. Previous to bring in the proposed framework, we first outline the 2 most generally applied impulse noise fashions used in this paper.

B. Gaussian Noise

It is uniformly dispersed over signal [Um98]. Here, in noisy image every pixel is combination of random Gaussian distributed degradations value and pixel value.

C. Salt and Pepper Noise

It has most effective two unique viable values. The each chance is classically not up to 0.1. It is kind of noise which is obvious in image. It represents as white and black pixels. Strong degradations discount system morphological or a median filter. The salt and pepper degradations are customarily prompted through pixel elements malfunctioning within the digital camera sensors. [6].

III. DENOISING FILTERS

3.1. Progressive Switching Median (PSM) Filter Method

A novel median-based switching clear out, called PSM filter, on this both noise clear out and impulse detector are using progressively in the iterative manner. A main benefit of such a technique is that some impulse pixels placed in large noise

blotches center also can be successfully detected and filtered.[22]

3.2. Median Filter Method

Median value is the worth in the center role of any taken care of series [7].

Image de-noising manner founded some median filter (MF) were proposed, some MF are software program oriented. Some of the large processes were explained underneath.

3.3. Simple Non Local Means Method (SNLM)

Mostly, the NL-method approach approximation an innocent depth as not unusual weighted for all pixel inside the picture, and the weighted proportional value. This technique is also to do away with aggregate of RVIN, SNP and GN. The nice answer may be to domestically various parameters, so that they're primly tuned to do away with the precise amount and diverse noises found in each part of the photograph [22].

3.4. Curvelet Based Non Local Means Method (CNLM)

The key to the CNLM technique dishonesty in similarity weight estimate. To describe the way to outline pixel similarity, we are able to take a look at the reconstructed picture corresponding characteristics to every curvelet scale. Provide a degradations image L_0 ; we 1st decompose it into n -scale curvelet coefficients (CC) applying Eqs. (7)–(13) (n value is define eith the aid of picture width [23]). Considering which curvelet transform (CT) maps the photograph noise into specific scales in the frequency area to gain rather little coefficients, it is simple to apprehend which the noise at the recon-strutted picture at every degree could be significantly attenuated in comparison with that in noisy picture. Therefore, those reconstructed images match weight founded on compute can make easy sup-urgent the noise have an effect on disadvantageous.

3.5. Self-Organizing Migration Algorithm (SOMA)

SOMA is depending on self-organizing person group's conduct in "social environment". Only location of the individuals within the investigated area is modified in the course of era called "migration loop". The algorithm, evolved through approach of prof. Zelinka in 1999. Numerous dissimilar description of SOMA exists. All primary each-to-One SOMA objectives essential for accurate information of the set of rules are explain beneath:

Parameter definition: Before beginning the set of rules, SOMA's parameters Step, Path Length, PopSize, PRT and the Cost Function required to be defined. The Cost Function is really a function which returns a scalar that may right away function a level of fitness.

Creation of Population: Population of humans is generated randomly. Each parameter for every separate ought to be selected randomly from the given range.

Migration loop: All people from populace (PopSize) is predicted via the Cost Function and the Leader (person with the best condition) is selected for the prevailing migration loop. Then all different people begin to bounce, (consistent with Step limitation description) in the course of the Leader. All individual is estimated in the end bounce applying the Cost Function. Jumping continues till a novel function described through Path Length has been reached [9].

3.6. Stein's Unbiased risk Estimator

Wavelet is a Multi-resolution Analysis (MRA) process eliminating data capable from an image (or a signal) space-frequency resolutions varying. If achieve a gray picture wavelet decomposition, because of wavelet representation sparsity, signal component is classically concentrated in a few high amplitude coefficients even as noise is spread uniformly throughout all coefficients. This bureaucracy the premise of wavelet shrinkage denoising. If we decrease to zero wavelet coefficients having amplitude less than a elect threshold value, most of the noise would be eliminated from the picture.

The main steps of wavelet shrinkage are:

1. Computing DWT of the original picture
2. Thresholding of wavelet coefficients.
3. Performing IDWT

IV. PROBLEM DEFINITION AND OBJECTIVE OF PROPOSED WORK

In previous curvelet based non local means (CNLM) method has many issues for removing high density noisy pixels. CNLM method removes noise on low density, but for the high density noise it did not work properly and image quality also degraded. And quality measures did not achieve good results in terms of PSNR, MSSIM and SSIM. For resolving these factors, suggest an evolutionary algorithm with an CNLM method for improving previous results. This proposed algorithm determined optimal set of parameters and refine the results. But the sometime previous method gives better result as equated to propose because of learning algorithm. It detects noise on small window size easily with high density noise.

V. PROPOSED METHODOLOGY

In the proposed work, implement the combination of SOMA and CNLM, the noisy pixels are locating in a pretty narrow range and therefore can decrease the opportunity of wrong finding. In the proposed system, the photograph to be denoised is divided into sub-imaginary. For any given $M \times M$ gray level image that is defined thru: $M \times M \rightarrow I$ where $I = [r, c]$ stand for the variety of pixel values. Pixel value at position (i, j) is given thru $F(i, j)$.

In the process of denoising requires selection of the kind of wavelet basis function (mother wavelet) to be used, the phase of decomposition and the threshold value for each level of decomposition. In this paper, we employ SOMA to find an optimal value for below variables. To find the optimal solution, we take threshold on the lower and upper value.

The parameters which govern the convergence and performance SOMA behavior are: [11]

- Various individuals and their dimension
- Various iterations (migration loops)
- Path Length: It position governs at which an separate will stop while leader following.
- Step Size: It decides the granularity of the path towards the leader.
- PRT: Pattern created applying this variable directs the

TABLE I. SET VARIABLES FOR OPTIMIZATION[12]

Variables to be optimized	Permitted Values
Types of Wavelet	Daubechies (db4, db6, db8), Symlet (sym4, sym6, sym8, sym10), Coiflet (coif2, coif4)
Decomposition Level	1-4
Threshold	It is estimated using lower and upper threshold

Proposed Algorithm

1. Consider 'I (x)' as the depth value of picture.
2. Add RVIN pixels into input picture, I at pixel position x and [d_{max}, d_{min}] the dynamic range of I. Dynamic range of gray levels image. For 8-bit pictures, d_{max} = 0 and d_{min} = 255. [4]

$$I_{noisy}(x) = \begin{cases} d_x & \text{with probability } r \\ I(X) & \text{with probability } (r - 1) \end{cases} \quad (1)$$

Here d_x is uniformly distributed in [d_{max}, d_{min}] and r defines the random-valued impulse noise level [5].

3. Add Gaussian distribution, probability distribution function is shaped of bell,

$$F(g) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(g-m)^2 / 2\sigma^2} \quad (2)$$

Where g (gray level), m (mean) or standard functions and σ is (standard deviation (SD)) of the noise. [6]

4. Consider that the gray degrees of any pixel value, in any window (wx) of size n Xn are represented by X₁, X₂, X₃, X₄, X₁ and it becomes X_{i1} ≥ X_{i2} ≥ X_{i3} ≥ X_{in} after sorting it in descending or in an ascending order

$$M_X = \text{Median}(W_X) = \begin{cases} X_{i(n+1)/2}; & n \text{ is odd} \\ \frac{1}{2} [X_{i(\frac{n}{2})} + X_{i(\frac{n}{2}+1)}]; & n \text{ is even} \end{cases} \quad (3)$$

5. Let fX f be length of the quest window "Ω", shaped through partitioning of an photograph. A general filtering window "Ω", is given in Eq. (4), it has rxr

matrix. The gray stage at any pixel (i,j) is stand for with the aid of I_(i,j)

$$\Omega = \begin{bmatrix} I_{1,1} & I_{(1, \frac{f+1}{2})} & I_{1,f} \\ I_{(\frac{f+1}{2}, 1)} & I_{(\frac{f+1}{2}, \frac{f+1}{2})} & I_{(\frac{f+1}{2}, f)} \\ I_{f,1} & I_{(f, \frac{f+1}{2})} & I_{f,f} \end{bmatrix} \quad (4)$$

6. NL- means approach estimation an innocent depth as commonplace weighted for all pixel in the photograph, and the weighted proportional value

$$NLM(i) = \frac{1}{C(i)} \sum_{j=\Omega} w(i, j) L_0(j) \quad (5)$$

Wherein Ω is the quest window and C(i) = ∑_{j=Ω} w(i, j) is a ordinary-ization constant; the weight w(i, j) indicates the matches among picture patches N(i) and N(j) (i.e., comparison windows) targeted at 2 pixels i and j.

7. Then, the reconstructed pictures are acquired the use of booking the CC at every scale and location the coefficients at closing scales to 0. Let L_q (1 ≤ q ≤ n) signify the reconstructed picture at qth level using the curvelet coefficients on the qth scale. The match weight amid pixels i and j inside the photo L_m (0 ≤ m ≤ n) might be defined as:

$$W_m(i, j) = \exp \left(- \frac{||L_m(N(i)) - L_m(N(j))||_2^2}{h_m^2} \right), \quad (6)$$

$$\text{where } h_m = \left(\frac{\text{med}(HH)}{0.6745} \right)$$

Where h_m is a constant comparative to the noise SD the image L_m which can be expected by the process used. med(HH) Is wavelet coefficient (Low pass filter and High pass filter).

$$\sum_{j=-\infty}^{\infty} w^2(2^j r) = 1 \quad r \in \left(\frac{3}{4}, \frac{3}{2} \right), \quad (7)$$

$$\sum_{l=-\infty}^{\infty} v^2(t - l) = 1 \quad r \in \left(-\frac{1}{2}, \frac{1}{2} \right), \quad (8)$$

$$U_j(r, \theta) = 2^{-\frac{3j}{4}} W(2^{-j} r) V \left(\frac{\frac{1j}{221\theta}}{2\pi} \right) \quad (9)$$

Where ij/21 is the integer part of j/2 W and V restriction the aid U_j to a polar wedge that is symmetric with appreciate to foundation. classify the waveform ϕ_j(x) thru means of its FT ϕ_j(w) = U_j(w). If equispaced rotation angles sequence θ₁ = 2π, l(0 ≤ θ₁ ≤ 2π), and order of translation parameters k = (k₁, k₂) ∈ Z² are introduced, the family of curvelets ϕ_{jLk} will be defined at scale 2^{-j}, orientation θ₁ and position x_k^(j,l) = R_{θ₁}⁻¹ (k₁. 2^{-j}, k₂. 2^{-j/2}) as:

$$\phi_{j,l,k} = \phi_j(R_{\theta_1}(x - x_k^{(i,j)})) \quad (10)$$

Where R_{θ} is the rotation matrix thru θ radians and R_{θ}^{-1} is its inverse defined as:

$$R_{\theta} = \begin{pmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{pmatrix} \quad (11)$$

8. The following difficulty integral make the CT of a function $f \in L_2(R^2)$:

$$c_{j,l,k} = (f, \phi_{j,l,k} = \int f(x) \phi_{j,l,k}(x) dx \quad (12)$$

9. The coefficients $c_{j,l,k}$ of the equation are understand like the decomposition into a bases of curvelet features $\phi_{j,l,k}$ [17].

$$\delta = \min(t, h_m \sqrt{2 \times \log(\text{no. of pixels})}) \quad (13)$$

Where, δ is estimated threshold, t is the threshold which is estimated using upper and lower value that minimizes Stein's unbiased hazard estimator and h_m is the SD of noise, which is estimated using Eqn 13 coefficients at 4th decomposition level). [10]

Finalize the parameters listed above in table I

10. Initialize the population and calculate all individual fitness.
11. Choose leader (individual with maximum fitness).
12. Create PRT vector with the aid of equation (14)

$$PRT_{vec}(i) = 1; \text{ if } r \text{ and } < PRT \text{ for each dimension} \quad (14)$$

13. Update the position of individuals using equation (15)

$$x_p^{l+1} \leftarrow x_p^l + (x_{leader}^{l+1} - x_{p,start}^{l+1}) \times step_size \times prtvec \quad (15)$$

14. Update fitness value and select new leader
15. Repeat steps 12 to 14 till a extinction condition is satisfied

VI. EXISTING TECHNIQUES

It presented that Dual Tree Complex Wavelet Transform (DT-CWT) with GCV is used which give ideal reconstruction over the conventional WT. Estimation is carried out in many parameters terms for example PSNR, mean Structural Similarity and Correlation Coefficient. The main weakness of this technique is better angular resolution which is not providing by DT-CWT and to overcome this problem 2D DTCWT method [13].

It supplied that growth denoising set of rules overall performance for commercial RT picture, an optimized wavelet denoising set of rules making use of hybrid noise model.

Smearing problem is main wavelet denoising algorithm problem [14].

It offered that an set of rules rely on WT and wiener clear out the use of log electricity distribution to denoised DI corrupted with the aid of Poisson-Gaussian noise. Poisson-Gaussian noise face some problem when a low level signal is expected, is very limited. Among the few contributions dealing with this problem [15].

It supplied that a singular way is proposed to dispose of GN found in fingerprint picture the usage of Stationary Wavelet Transform, a threshold founded on Golden Ratio and weighted median. A disadvantage is a completely massive redundancy and elevated computational complexity. The lack of directionality and oscillating persist because the stationary wavelet remodel is relying upon a filter out bank structure [16].

It presented that IR imaginary most have vague details and low resolution, resulting in poor visual effect and lower image quality. One weakness of K-SVD is that at the same time as doing well in reconstruction, it lacks discrimination functionality to separate special lessons. K-SVD requires massive garage because the computed non-0 coefficients reside in specific locations [17].

It provided that Non-neighborhood Means filters and diffusion tensor technique combination in 3D image denoising region. Non-local means algorithm is improved by taking symmetry advantage in weights and through applying a lookup table to speed up the weight computations. Diffusion pictures are sensitive to water diffusion that is in the 5-10 μ_m order at the time of size time. If this happens, images are sometimes full of ghosting because of the water molecules encountering obstacles. Because of this, DTI need at least 7 tensor fittings, requires wide computing power, man-hours, and expertise [18].

It presented that a novel imaginary denoising way depend on the mixture of SWT and bilateral filter. The essential giving of this paper is inside the utilization of a brand new neighborhood association to broaden a brand new multiscale bilateral clear out. The some trouble in this paper first is Gradient reversal - creation of false edges within the imaginary and second is Staircase impact - intensity plateaus that result in imaginary performing like cartoons [19].

It presented that denoising earlier demosaicking strategy is exploited. Some problem find out in this paper Signal and noise must both be random, numerous programs have a deterministic signal and random noise and Extend Wiener clear out (or Phillips method) to allow deterministic signal [20].

It presented that the algorithm depend on stack to eliminate the small vicinity noises in binary microalgae picture. The

denoising of picture is accomplished via using this set of regulations via scanning picture one time. The new algorithm now not handiest conserves sign's authentic capabilities; however additionally has stronger capacity to cast off noise. The numerical experiments have illustrate that the set of rules is very powerful in noise discount, and is higher than conventional approach in complexity and running time of the image denoising. This technique better result provide binary image not for another varieties of image [21].

VII. COMPARATIVE TABLES

The experimental outcomes have been implementing using MATLAB12 on Image Processing. The outcomes have been experienced on gray scale with dissimilar varieties of format images of size 256 X256. The evaluation of the proposed method is obtained on the basis of PSNR, SSIM and MSSIM. We have implemented image denoising on various images corrupted with RVIN, Gaussian noise (GN) and pepper and salt noise on different noise density. It is varying from 10% to 90%. The denoised images are evaluated using three criteria mentioned below: For the de-noised image "Z", of size M X M, the PSNR is given by:

A. *PSNR*: It is exploited to measure the visible best of the denoised photograph in comparison to the particular picture. Compute PSNR and MSE value of a denoised and unique image.

$$MSE(x) = \frac{1}{M} ||I - Z||^2 = \frac{1}{M} \sum_{i=1}^M (I - Z)^2 \quad (16)$$

Where I is the original image

$$PSNR(x) = \frac{10 \log((double(m))^2)}{MSE(x)} \quad (17)$$

Where m is the original picture maximum value.

B. *Structural Similarity Matrix (SSIM)*- It is used for calculating similarity content between original image and denoised image.

$$SSIM = \frac{(2\mu_x\mu_y - c_1)(2\sigma_{xy} - c_2)}{(\mu_x^2 - \mu_y^2 - c_1)(\sigma_x^2 - \sigma_y^2 - c_2)} \quad (18)$$

Where μ_x is the average of x, μ_y is the average of y, σ_{xy} is the covariance of x and y, $c_1 = (K_1 L)^2$, $c_2 = (K_2 L)^2$, $K_1 = 0.01$ and $K_2 = 0.03$ by default and L is the dynamic variety of pixel values.

C. *MSSIM*-

$$MSSIM(E, F) = \frac{\sum_{k=1}^R SSIM(x, y)}{R} \quad (19)$$

Where R is the entire number of local windows in the picture, E and F signify the unique picture and the denoised image, respectively; x and y are the picture contents at the k-th local window in the real and denoised pictures

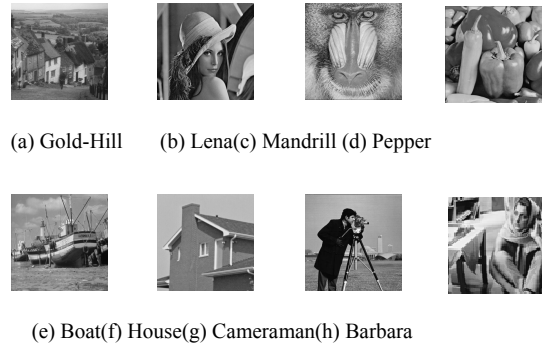


Fig. 1. Grayscale test original images of 8-bit per pixel.

TABLE II. DIFFERENT TECHNIQUES EVALUATE PSNR (DB) AND MSSIM OVER THREE DEGRADED IMAGES BY GAUSSIAN NOISE USING $\sigma = 40$ (WHERE PSNR VALUE IS THE LEFT OF '/')

Method	Boat $\sigma = 40$	Pepper $\sigma = 40$	Lena $\sigma = 40$
MED[7]	13.27/0.891	13.79/0.881	15.33/0.893
PSMF[8]	12.70/0.873	13.15/0.860	15.31/0.902
NLM[21]	6.91/0.592	7.34/0.592	8.97/0.597
CNLM[23]	17.98/0.977	18.88/0.972	19.85/0.982
Proposed	37.49/1.004	38.50/1.003	38.21/1.006

TABLE III. DIFFERENT TECHNIQUES EVALUATE PSNR (DB) AND MSSIM OVER THREE DEGRADED IMAGES BY GAUSSIAN NOISE USING $\sigma = 70$ (WHERE PSNR VALUE IS THE LEFT OF '/')

Method	Boat $\sigma = 70$	Pepper $\sigma = 70$	Lena $\sigma = 70$
MED	13.54/0.890	14.03/0.892	15.67/0.899
PSMF	12.94/0.871	13.35/0.872	15.60/0.903
NLM	7.20/0.605	7.64/0.607	9.303/0.610
CNLM	18.06/0.975	18.76/0.972	20.26/0.984
Proposed	37.68/1.004	38.71/1.004	37.84/1.006

TABLE IV. DIFFERENT TECHNIQUES EVALUATE PSNR (DB) AND MSSIM OVER THREE DEGRADED IMAGES BY GAUSSIAN NOISE USING $\sigma = 90$ (WHERE PSNR VALUE IS THE LEFT OF '/')

Method	Boat $\sigma = 90$	Pepper $\sigma = 90$	Lena $\sigma = 90$
MED	13.73/0.902	14.32/0.901	15.75/0.899
PSMF	13.10/0.882	13.61/0.881	15.66/0.903
NLM	7.43/0.623	7.78/0.617	9.46/0.618
CNLM	18.37/0.983	19.30/0.982	20.36/0.977
Proposed	37.57/1.004	38.64/1.003	37.99/1.006

TABLE V. DIFFERENT TECHNIQUES EVALUATE PSNR (DB) AND MSSIM OVER THREE DEGRADED IMAGES BY RVIN NOISE USING $\sigma = 40$ (WHERE PSNR VALUE IS THE LEFT OF '/')

Method	Boat $\sigma = 40$	Pepper $\sigma = 40$	Lena $\sigma = 40$
MED	22.62/1.018	22.96/1.011	21.97/0.971
PSMF	23.04/1.007	23.33/1.004	22.71/0.977
NLM	14.28/0.974	13.85/0.931	13.40/0.790
CNLM	18.74/1.074	18.42/1.043	17.57/0.906
Proposed	37.54/1.003	39.28/1.001	38.21/1.003

TABLE VI. DIFFERENT TECHNIQUES EVALUATE PSNR (DB) AND MSSIM OVER THREE DEGRADED IMAGES BY RVIN NOISE USING $\sigma = 70$ (WHERE PSNR VALUE IS THE LEFT OF '/')

Method	Boat $\sigma = 70$	Pepper $\sigma = 70$	Lena $\sigma = 70$
MED	16.64/1.039	15.89/1.018	15.00/0.839
PSMF	16.85/1.018	16.21/1.009	15.34/0.852
NLM	11.68/0.939	11.20/0.883	10.67/0.660
CNLM	16.84/1.122	15.81/1.071	14.75/0.822
Proposed	37.67/1.003	38.63/1.003	38.07/1.005

TABLE VII. DIFFERENT TECHNIQUES EVALUATE PSNR (DB) AND MSSIM OVER THREE DEGRADED IMAGES BY RVIN NOISE USING $\sigma = 90$ (WHERE PSNR VALUE IS THE LEFT OF '/')

Method	Boat $\sigma = 90$	Pepper $\sigma = 90$	Lena $\sigma = 90$
MED	13.78/0.897	12.96/0.991	12.00/0.722
PSMF	13.13/0.878	12.96/0.986	12.03/0.725
NLM	7.38/0.616	9.98/0.837	9.38/0.594
CNLM	18.44/0.977	14.16/1.050	12.93/0.753
Proposed	37.37/1.004	38.71/1.003	37.81/1.006

TABLE VIII. DIFFERENT TECHNIQUES EVALUATE PSNR (DB) AND MSSIM OVER THREE DEGRADED IMAGES USING $\sigma = 40$ (WHERE PSNR VALUE IS THE LEFT OF '/')

Method	Boat $\sigma = 40$	Pepper $\sigma = 40$	Lena $\sigma = 40$
MED	18.07/0.980	18.56/0.980	18.04/0.941
PSMF	22.14/1.002	22.97/1.003	22.98/1.004
NLM	9.99/0.811	9.72/0.768	9.40/0.605
CNLM	18.50/1.076	18.09/1.053	17.35/0.901
Proposed	37.57/1.003	38.83/1.003	37.79/1.005

TABLE IX. DIFFERENT TECHNIQUES EVALUATE PSNR (DB) AND MSSIM OVER THREE DEGRADED IMAGES USING $\sigma = 70$ (WHERE PSNR VALUE IS THE LEFT OF '/')

Method	Boat $\sigma = 70$	Pepper $\sigma = 70$	Lena $\sigma = 70$
MED	9.89/0.818	9.89/0.765	9.67/0.624
PSMF	9.86/0.815	9.86/0.760	9.633/0.622
NLM	7.26/0.678	7.09/0.623	6.90/0.461
CNLM	16.15/1.118	15.36/1.046	14.42/0.809
Proposed	37.74/1.004	38.78/1.003	38.18/1.006

TABLE X. DIFFERENT TECHNIQUES EVALUATE PSNR (DB) AND MSSIM OVER THREE DEGRADED IMAGES USING $\sigma = 90$ (WHERE PSNR VALUE IS THE LEFT OF '/')

Method	Boat $\sigma = 90$	Pepper $\sigma = 90$	Lena $\sigma = 90$
MED	6.63/0.653	6.57/0.606	6.37/0.433
PSMF	6.62/0.652	6.56/0.603	6.36/0.432
NLM	6.02/0.610	5.85/0.560	5.67/0.391
CNLM	14.73/1.128	13.72/1.044	12.69/0.741
Proposed	37.65/1.004	38.79/1.004	37.87/1.005

VIII. RESULT ANALYSIS

Fig. 2 indicates the PSNR and MSSIM values for the compared filters in use on the despoiled Boat picture on Gaussian Noise (40% noise density) and proposed filter out proved higher than different filters. Tables 2 to Table four listing the PSNR and MSSIM values of all the estimate strategies operating on pix Boat, Pepper and Lena with $\sigma = 40$ to $\sigma = 90$, the use of Gaussian noise respectively. Obviously, the SOMACNLM filter proved better than other evaluated filters in terms of PSNR and MSSIM. Tables five to Table 7 list the PSNR and MSSIM values of all the evaluated procedures running on photographs Boat, Pepper and Lena with $\sigma = 40$ to $\sigma = 90$, the use of Impulse noise respectively. Tables 8 to Table 10 list the PSNR and MSSIM values of all the evaluated approaches in use on pictures Boat, Pepper and Lena with $\sigma = 40$ to $\sigma = 90$, using SNP noise respectively. When increases the noise density, then PSNR and MSSIM decreases for all filters, but proposed shown in Tables it gives improve value of PSNR and MSSIM at high density. As shown, proposed filter proved much high PSNR and MSSIM as equated to extra denoising filters. Outcomes obtained using various de-noising filters for Lena picture are illustrate in Fig 6 to Fig 9 on high density noise with all variety of noise and proposed filter shows better results on each noise and noise density. In Table 2, PSNR and MSSIM values acquired via extraordinary median filter and non nearby means primarily based de-noising process for Boat, Pepper and Lena picture are proven. As match up to PSMF filtering founded-noising, proposed technique results in a progress of PSNR/MSSIM varies from 37.49/ 1.004 to 38.21/1.006. The PSNR end result of the proposed technique is superior to each the another

approaches for noise densities up to 90%. The presentation of our proposed scheme, allowing for eight test pictures corrupted thru RVIN, GN and SNP noise is represented in Tables and Fig. 1 to Fig 9. Fig. 1 to Fig 9. In Fig. 2 to Fig nine, it's miles virtually seen that the presentation curve of our proposed manner is well higher than the prevailing de-noising filters. Between the existing schemes, CNLM filter shows the best results. On 3X3 window size reached the PSNR/MSSIM value high up to 90% noise density. The performance is dependent on image with add to in window size; number of pixels in any window will enhance which leads to better difficulty and time intake. For lower noise density, numerous pixels despoiled through noise are tons much less which ends up in excessive PSNR cost with lesser length of window. For maximum noise densities various pixels corrupted thru noise are substantial consequently the de-noised photograph PSNR with higher window length achieves higher fee because of higher accuracy on account of greater number of pixels underneath attention for finding of noise at any particular pixel. The higher noise density is removed by our proposed method because optimum solution. Image results several filters on Lena picture for 90% noise corruption through Gaussian Noise on 3X3 window are given in Fig. 7. PSNR/MSSIM cost of our proposed process is considered as 39.28/1.001dB, which is the nice among all. Further in Fig. Five the outcomes of Pepper picture are specified for 90% noise density on GN. Proposed scheme present the PSNR/MSSIM of 38.64/1.003 dB at this level. Figs. 8 and 9 show the outcomes of dissimilar filters in restoring Lena image tainted thru 90% noise density which is degraded using RVIN and SNP noise respectively. The restored picture first-rate of the proposed technique is the best, both quantitatively.

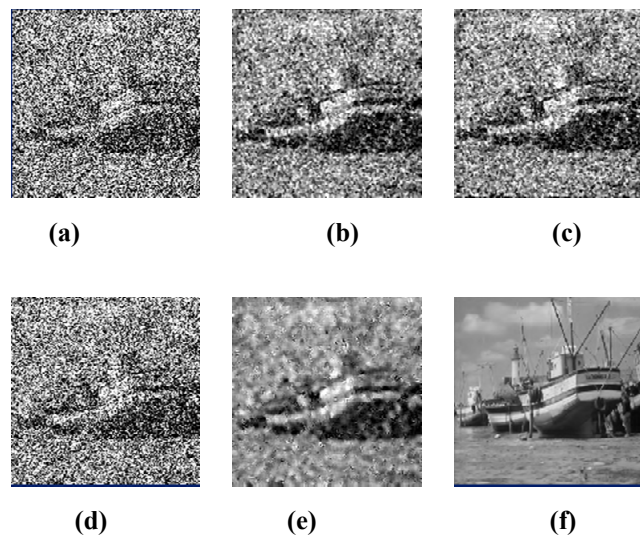


Fig. 2. Results of different filters in restoring Gaussian Noise 40% corrupted Boat image: (a) Noisy picture, (b) MED, (c) PSMF, (d) NLM, (e) CNLM (f) Proposed technique.

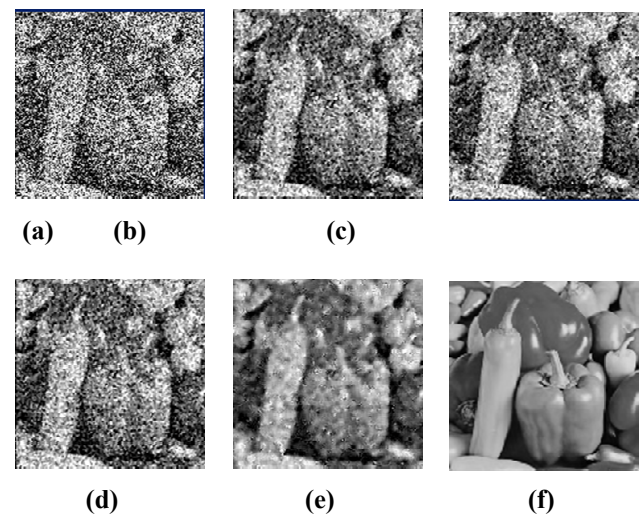


Fig. 3. Results of different filters in restoring Gaussian Noise 40% corrupted Pepper picture: (a) Noisy Image, (b) MED, (c) PSMF, (d) NLM, (e) CNLM (f) Proposed method.

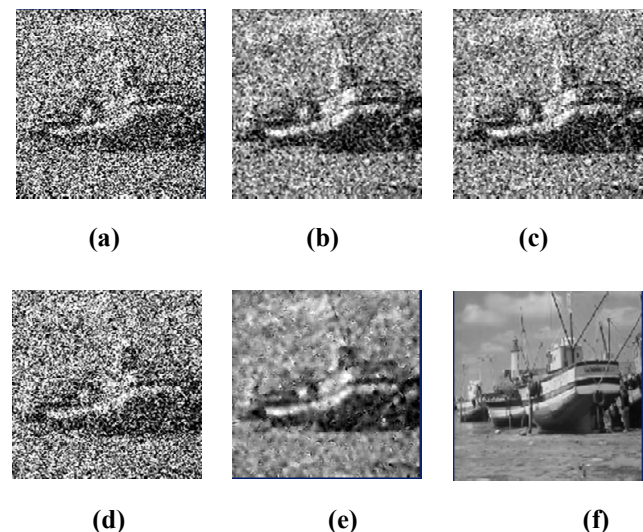


Fig. 4. Results of dissimilar filters in restoring Gaussian Noise 90% corrupted Lena image: (a) Noisy picture, (b) MED, (c) PSMF, (d) NLM, (e) CNLM (f) Proposed process.

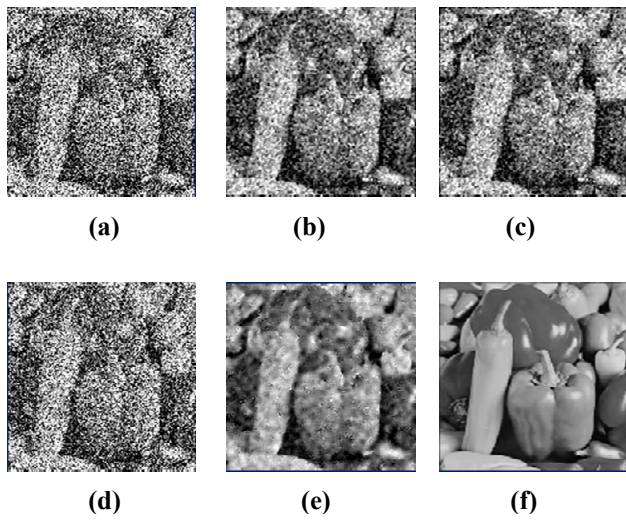


Fig. 5. Results of different filters in restoring Gaussian Noise 90% corrupted Pepper image: (a) Noisy Image, (b) MED , (c) PSMF, (d) NLM , (e) CNLM (f) Proposed method.

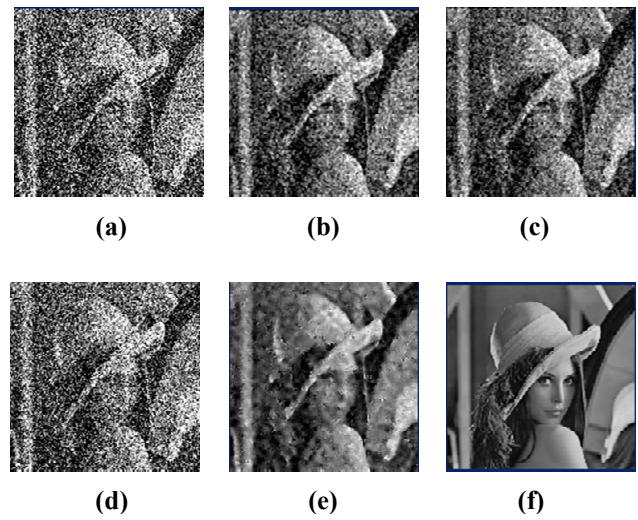


Fig. 7. Results of dissimilar filters in restoring Gaussian Noise 90% degraded Lena picture: (a) Noisy Image, (b) MED , (c) PSMF, (d) NLM , (e) CNLM (f) Proposed technique.

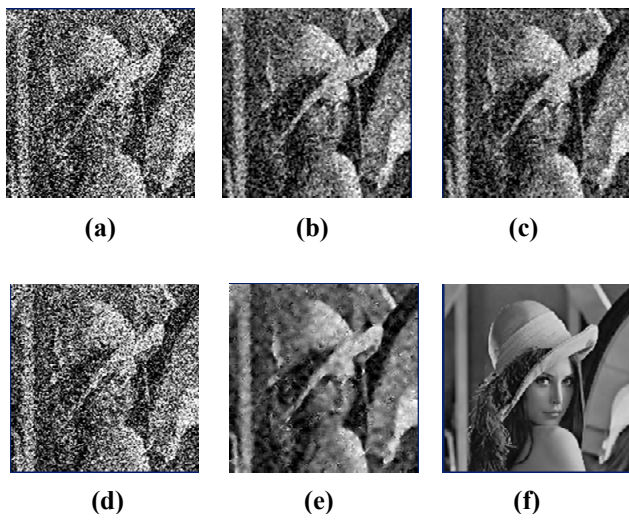


Fig. 6. Results of dissimilar filters in restoring Gaussian Noise 40% degraded Lena picture: (a) Noisy Image, (b) MED , (c) PSMF, (d) NLM , (e) CNLM (f) Proposed method.

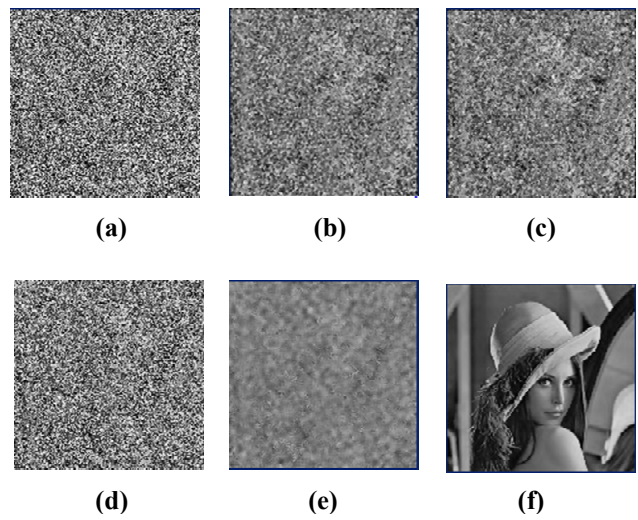


Fig. 8. Results of dissimilar filters in restoring Impulse Noise 90% corrupted Lena image: (a) Noisy picture, (b) MED , (c) PSMF, (d) NLM , (e) CNLM (f) Proposed scheme.

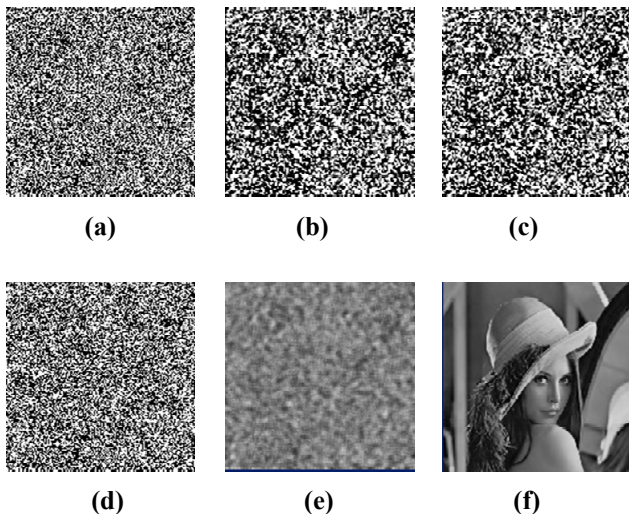


Fig. 9. Results of different filters in restoring SNP Noise 90% degraded Lena image: (a) Noisy picture, (b) MED, (c) PSMF, (d) NLM, (e) CNLM, (f) Proposed method.

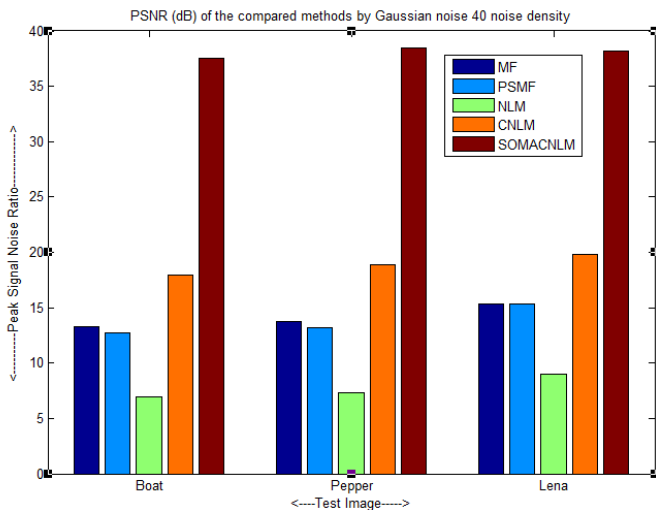


Fig. 10. Comparison chart of PSNR show of dissimilar filters specified in Table 1.

The observation from Fig. 10 shows that the CNLM methods can't suppress noise efficiently, the NLM method cause photograph over-smoothing near the edges and inside the textural regions, the CNLM process produces artifacts. By comparison, the SOMACNLM scheme offers the pleasant healing outcomes in that it may suppress noise efficiently even as pre-serving picture information regardless of in smooth areas or element areas.

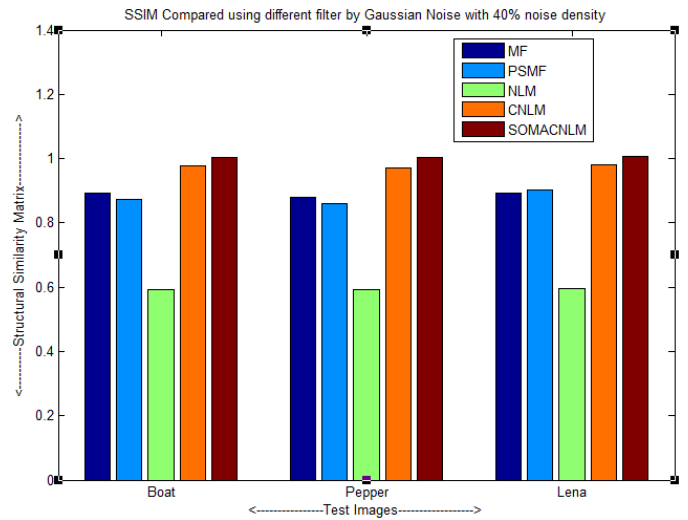


Fig. 11. Comparison chart of SSIM show of dissimilar filters specified in Table 1.

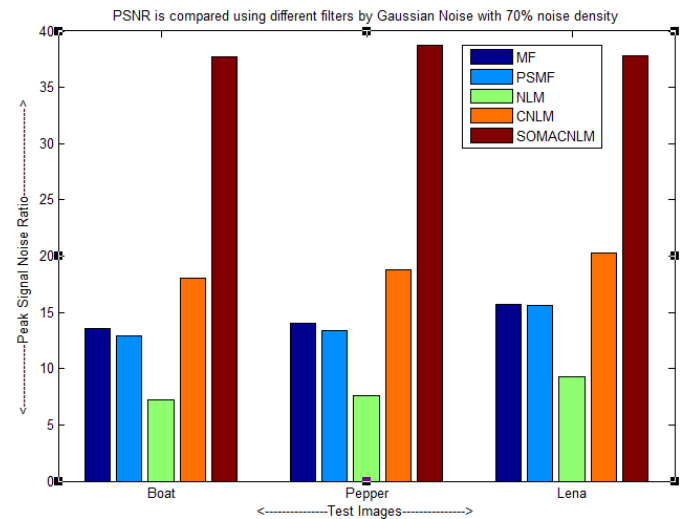


Fig. 12. Comparison chart of PSNR show of dissimilar filters specified in Table 2.

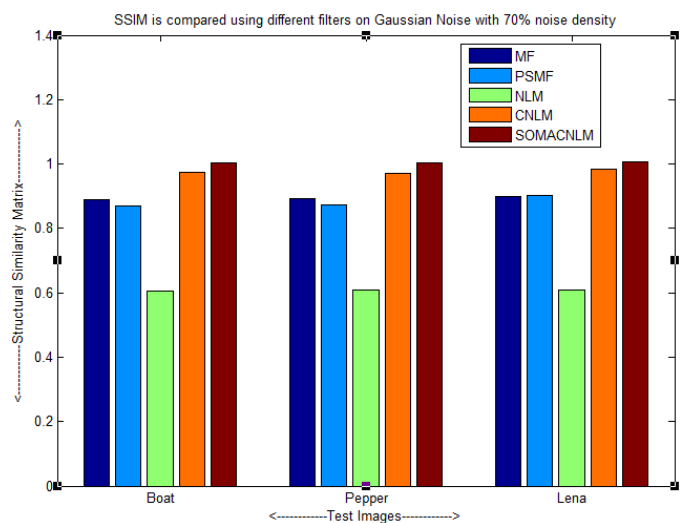


Fig. 13. Comparison chart of SSIM show of dissimilar filters specified in Table 2.

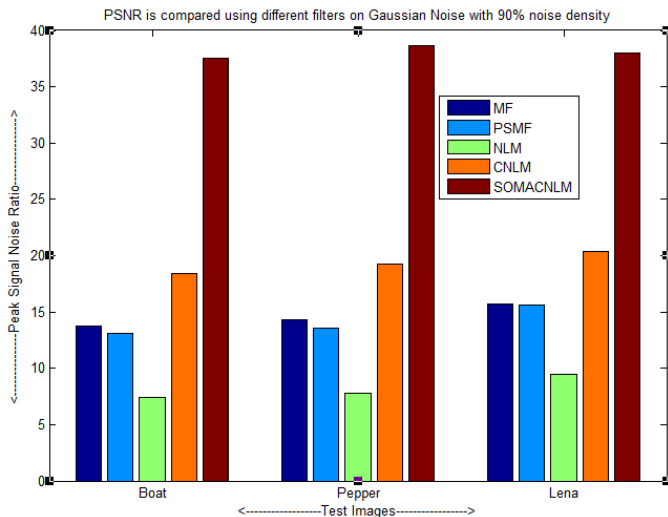


Fig. 14. Comparative chart of PSNR performance of different filters given in Table 3.

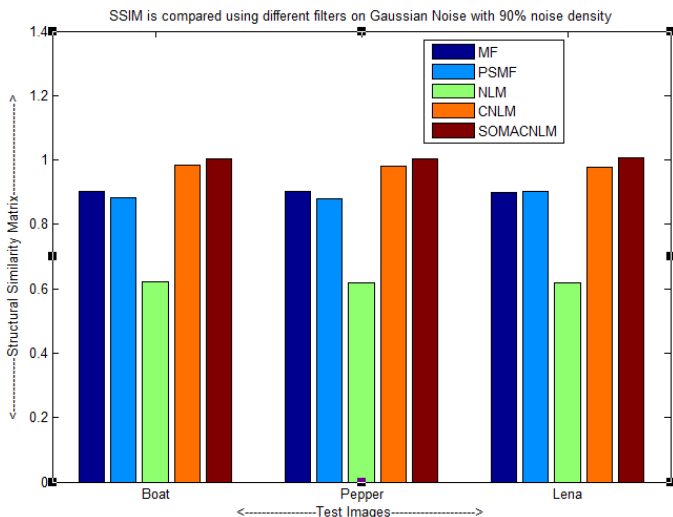


Fig. 15. Comparison chart of SSIM performance of dissimilar filters specified in Table 3.

IX. CONCLUSION

In this paper define an algorithm SOMACNLM for image denoising. The proposed technique finds the pixels similarity in the degradations imaginary depend on the numerous curvelet levels images produced and the degradations picture in keeping with the conjecture noise well-known deviation in noisy picture. The simulations have established that the proposed set of rules better the kingdom-of-art denoising processes in noise elimination phrases and element protection due to its efficiency in calculating pixel comparison and most suitable answer. This research proposed and discovers a new concept for image denoising exploiting SOMA and CNLM. There are two essential steps on this set of rules: first is Noise finding and second is Noise Removal. In noise detection step,

the idea of minimum and maximum of degradations pixels in a picture is used which offers higher noise finding capability and effectiveness. The experimental outcome presented which the proposed method of SOMACNLM is considerably superior various state-of-the-art schemes, both quantitatively and visually. This research proved that the image quality from 37.49% to 39.28% for 40% noise density. We have shown in this paper that SOMA is a good set of rules to locate a surest set of parameters for CNLM denoising. The simulation results, and associated evaluation criteria represent that our method generates good results, much better than existing work. It helps in noise removal along with preservation of fine details much better than that obtained with other methods. This work can be further extended to optimization algorithm use. Optimization techniques may also be used to get better convergence problems and quality of solution. Also this work can be implementing on different type of noise and satellite images.

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